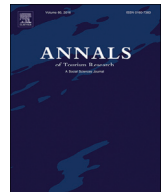




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COVID-19 and the aviation industry: The interrelationship between the spread of the COVID-19 pandemic and the frequency of flights on the EU market[☆]

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ABSTRACT

This study aims to investigate the contribution of aviation related travel restrictions to control the spread of COVID-19 in Europe by using quasi-experiment approaches including the regression discontinuity design and a two-stage spatial Durbin model with an instrumental variable. The study provides concrete evidence that the severe curtailing of flights had a spontaneous impact in controlling the spread of COVID-19. The counterfactual analysis encapsulated the spillover effects deduced that a 1% decrease in flight frequency can decrease the number of confirmed cases by 0.908%. The study also reveals that during the lockdown, the aviation industry cancelled over 795,000 flights, which resulted in averting an additional six million people being from being infected and saving 101,309 lives.

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Introduction

An airborne disease called Coronavirus (COVID-19) has to date been the biggest game-changer in terms of sheer devastation for both the aviation and tourism industries. In the hundred years prior to this, the airline industry experienced a sustained and unprecedented growth, even in the face of previous global catastrophes, such as the 9/11 terrorist attacks in 2001 and the global financial crisis of 2008. The air travel market took 50 years to reach the milestone of one billion passengers in 1987 and then experienced exponential growth within less than two decades, surpassing two billion by 2005, three billion by 2013, and reaching the milestone of 4.5 billion passengers by 2019 (O'Connell, 2019). The combination of low airfares and a growing prosperous middle-class population has largely changed the dynamics of international travel, as evidenced by the fact that the market share of air travel surged to 58% by 2019, 14% more than the number 20 years ago (UNTWO, 2020).

However, the aviation world then abruptly changed in early 2020 due to the outbreak and subsequent rapid spread of COVID-19 that impacted the world within a few months. Since it was first identified in Wuhan, China at the end of 2019, the pandemic spread to 218 countries globally in a few months (Lai, Shih, Ko, Tang, & Hsueh, 2020). By April 2020, more than one million people around the globe had been infected. Seven months later, in late November, the confirmed cases had rapidly soared to over 53 million individuals, with over 1.38 million deaths (Johns Hopkins University, 2020). Besides the travel bans set up by countries globally, people's reluctance to travel during a global pandemic has had a consequent damaging impact on the aviation and

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tourism sectors. Tourists are more likely to postpone or cancel their travel plans in order to minimise the risk of becoming infected (Reisinger & Mavondo, 2005), and this is an outlook that is now embedded in the psyche of today's tourists is the compulsion to avoid disease-affected destinations and this all influences tourism outcomes (Jonas, Mansfeld, Paz, & Potasman, 2011; Lepp & Gibson, 2003; Page, 2009; Zhang, Hou, & Li, 2020).

Although the damaging impact of the pandemic on the air travel industry has drawn attention from scholars (e.g. Gallego & Font, 2020; Gössling, Scott, & Hall, 2020; Graham, Kremarik, & Kruse, 2020; Hall, Scott, & Gössling, 2020; Iacus, Natale, Santamaria, Spyros, & Vespe, 2020; Suau-Sanchez, Voltes-Dorta, & Cuguero-Escofet, 2020), an empirically derived study offering an understanding of the impact of travel restrictions on flight frequency has not been undertaken. Using a quasi-experimental impact evaluation method, this paper aims to investigate the impact of travel restrictions (i.e. national lockdowns) on flight frequency and their consequential yet counterfactual effect on the spread of COVID-19 using two-stage spatial modelling in the context of Europe (hereafter, Europe stands for 27 EU countries plus Iceland, Norway, Switzerland and the UK).

The originality of this study can be established in two ways. Firstly, this is one of the few tourism studies to address the impact of COVID-19 on the aviation industry, particularly on flight frequency and its impact on the spread of the infection, which enriches the crisis management theories in the tourism literature. Secondly, from the methodological perspective, the application of quasi-experimental methods such as regression discontinuity design, which can be used to estimate the counterfactual effect, is limited in the tourism literature. Yet, this study uses the regression discontinuity design to estimate the impact of travel restrictions on flight frequency. It also provides further spatial modelling with an instrumental variable to examine the consequential impact on the number of infected cases in order to understand the implications of travel restrictions – specifically the restrictions placed on international flights – for the number of lives saved by restricting international flights.

The remainder of the paper is organised as follows. The Literature review section reviews the relevant literature on travel restrictions and the implications of COVID-19 for the aviation and tourism industry. Methodology and data section presents the methodology and data used for this study. The Findings and discussions section presents and analyses the empirical findings, supported by relevant discussion and literature, while the Conclusions section concludes the paper.

Literature review

The impact of COVID-19 on the aviation/tourism industry

Scholars have revealed that air transport facilitates the spread of pandemics throughout the world (Tatem, Rogers, & Hay, 2006; Wilder-Smith, Paton, & Goh, 2003). Moreover, some researchers have discovered that airline travel could influence the spread of viruses such as the following: influenza (Grais, Ellis, & Glass, 2003), Severe Acute Respiratory Syndrome (SARS) (McLean, May, Pattison, & Weiss, 2005), Ebola (Bogoch et al., 2015), Zika (Bogoch et al., 2016), and Dengue (Tian et al., 2017). Oztig and Askin (2020) reported that SARS spread to 37 countries (8000 cases) while the Middle East respiratory syndrome spread to 27 countries (2494 cases) and the transmission was partially exacerbated by people taking flights. As Wilder-Smith (2006) reported, the avian flu (H5N1) outbreak spread to around 60 countries and caused 191 deaths but resulted in a reduction of about 12 million tourist arrivals in the Asia Pacific region.

Wen, Gu, and Kavanaugh (2005) revealed that SARS had an adverse effect on tourists' willingness to travel due to the health risk associated with the travel activities. Kuo, Chen, Tseng, Ju, and Huang (2008) confirmed Wen, Gu, and Kavanaugh's (2005) finding by observing a significant shrinkage in the number of visitor arrivals to countries affected by SARS. Rosselló, Santana-Gallego, and Awan (2017) quantified the impact of different pandemics on visitor arrivals using the econometric method. They revealed that the outbreak of the pandemic significantly pushed down the visitor numbers. For example, the spread of malaria reduced the number of visitor arrivals by 47%. Blake, Sinclair, and Sugiyarto (2003) showed that the foot and mouth disease reduced the tourism receipts in the UK. It is apparent that the aviation and tourism sectors are highly vulnerable to infectious disease outbreaks due to their face-to-face and contact-intensive nature and the high mobilities of people and goods within and between national borders.

However, the COVID-19 pandemic has surpassed all the previous pandemics as it has extended to more than 200 countries and the aviation industry has contributed to the spread of the pandemic (Sun, Wandelt, & Zhang, 2020). The COVID-19 pandemic has produced an unprecedented commercial catastrophe for the world's airline industry. Global traffic levels fell by 21% in March 2020, compared to the same month a year earlier, followed by an abrupt escalation leading to a further contraction as global traffic levels further declined to reach 66% by April. The downward trajectory continued to alarming levels by further decreasing to 69% by May as the destructive shockwaves proliferated throughout the world, with the knowledge that this contagious transmittable virus can be fatal within a short timeframe of a person becoming infected. The 'fear factor' was continuously gathering momentum in society. UNTWO (2020) estimated that international tourist arrivals would decline by 70% in 2020, which represented a 700 million and US\$730 billion loss in visitor numbers and tourism receipts in the inbound tourism market, respectively. The loss caused by COVID-19 in 2020 was eight times more than that of the Global Financial Crisis of 2008/09 (UNTWO, 2020).

From an aviation viewpoint, the situation is mirrored, as airline passenger revenues were estimated to drop by 69% in 2020, which is equivalent to a US\$421 billion loss, compared to the pre-pandemic year of 2019, while aggregated losses were expected to be around US\$118 billion, which is over four times more than the losses that the industry experienced after the global financial crisis of 2009 (IATA, 2020b). COVID-19 has become the severest threat to the airline industry in history (Amankwah-Amoah, 2020) and the impact may last until no earlier than 2024 (IATA, 2020a). Gudmundsson, Cattaneo, and Redondi (2020) predicted a similar recovery path with mid-2022 as the optimal scenario and 2026 as the most pessimistic scenario, respectively. From a

global tourism and hospitality industry viewpoint, this view has resonated with some researchers who have gone as far as to state that the pandemic may even entirely ruin the international tourism market (Thams, Zech, Rempel, & Ayia-Koi, 2020).

The impact of travel restrictions on the tourism/aviation industry

The tourism and aviation industries are highly vulnerable to infectious disease outbreaks. When COVID-19 started to spread between people and between national and international spaces, countries and authorities started to restrict travel and close their borders during the outbreak to minimise the spread of the disease and limit both the importation and exportation of the disease via tourists (Luo, Imai, & Dorigatti, 2020; Vaidya, Herten-Crabb, Spenser, Moon, & Lillywhite, 2020). In recent decades, air travel has become increasingly more affordable and the consumer has an ample selection of airlines to choose from, equipped with an array of different value-adding flight products. However, the transmission of the disease can only be curtailed by restricting travel and mobility, which has prompted governments to rapidly enact legislation.

According to the UNTWO (2020), 90 destinations had completely or partially suspended inbound tourism and another 44 destinations had closed their borders to selected countries of origin. Governments around the globe have imposed these travel bans, lockdowns, stay-at-home directives and shutdowns in order to control the spread of the virus (Luo, Imai, & Dorigatti, 2020). Sun, Wandelt, and Zhang (2020) noted that this has been conducted in a highly uncoordinated and almost chaotic manner. Taylor (2020) and Salari, Milne, Delcea, Kattan, and Cotfa (2020) argued that the various inconsistent travel restrictions reduced the number of visitors who intended to fly by air during the COVID-19 pandemic.

The UNTWO (2020) stated that it was the first time that international travel had been restricted in such a way with so many destinations imposing travel restrictions. Many potential passengers that were aiming to travel were either discouraged from doing so or informed that they would only be allowed entry if they adhered to a specific quarantine that could last for up to two weeks at their own expense. Consequently, this had enormous knock-on ramifications; as Adrienne, Budd, and Ison (2020) reported, by mid-April 2020, the air travel market had shrunk by 64%, as 17,000 aircraft had been consigned to their hangars. Airlines had to minimise their flight operations and cut their costs due to the travel restrictions.

With the uneven implementation of the vaccination programme across the world, the only available tools became narrowed down to measures such as control and containment that include social distancing, quarantining and travel restrictions (i.e. lockdown) to minimise the spread of an infectious disease such as COVID-19 (Kim & Liu, 2021; Lau et al., 2020; Petersen et al., 2020). Past studies have empirically proven that travel restrictions and control measures have been effective in minimising the spread of infectious diseases. Hufnagel, Brockmann, and Geisel (2004) argued that isolating large cities was an effective control measure of the SARS epidemic. Brownstein, Wolfe, and Mandl (2006) examined the spread of influenza within the USA and highlighted the importance of flight restrictions as there was a significantly delayed timeframe before influenza peaked in 2001–2002, which was directly attributable to operating a reduced flight schedule, whereas, in France, the opposite took place as there were no flight restrictions imposed, which consequently accelerated the spread of influenza. Yet, based on a two-city dispersal model of avian influenza spread via air travel, Tuncer and Le (2014) argued that the effectiveness of control measures (e.g. isolation and quarantining) heavily depends on the air travel rate, i.e. the proportion of air passengers based on the population of the departure city. Thus, travel restrictions are key to reducing pandemic prevalence.

However, there are also counter arguments that travel restrictions are ineffective in controlling the spread of infectious diseases. Cooper, Pitman, Edmunds, and Gay (2006) found that travel restrictions did not significantly delay the international spread of the influenza pandemic due to the initial large number of infected people and the fast growth rate of the confirmed cases. Similarly, Ferguson et al. (2006) found that they can only slow down the spread for less than 2–3 weeks. Chinazzi et al. (2020) used a population transmission model to investigate the relationship between travel restrictions and the spread of COVID-19. They found that the Wuhan lockdown was not as effective as the global travel restrictions which delayed the spread of the virus to other countries until mid-February 2020. Additionally, it is acknowledged that the virus can spread at a domestic level through regular daily mobility, such as traveling to work or school, visiting hospitals and conducting social activities (Borkowski, Jażdżewska-Gutta, & Szmelter-Jarosz, 2021; Zhang et al., 2021). However, this lies outside the scope of the current study, which focusses on the cross-border flight transmission of the virus, and thus mobility at the daily and domestic level is not explored in the analysis.

In the tourism literature, many scholars have shed light on the impact of COVID-19 on the tourism industry (Qiu, Park, Li, & Song, 2020; Yang, Zhang, & Chen, 2020) and predicted the recovery path (Liu, Vici, Ramos, Giannoni, & Blake, 2021; Qiu et al., 2021), but the aviation industry has not been subjected to such close scrutiny. Yet, travel restrictions have been set up globally to control the spread of COVID-19, and the negative catalytic implications for the aviation and tourism industries are far-reaching. Since the contribution of aviation related travel restrictions to control the spread of COVID-19 has not been investigated by tourism scholars, this current study aims to address the area.

Methodology and data

Regression discontinuity design

In this research, to examine the impact of travel restriction on the number of flights to selected European countries, a regression discontinuity design model is adopted:

$$\ln Flight_{it} = Constant + \tau \cdot Travel\ Restriction_t + \phi \cdot F(R_t) + \delta \cdot \ln GDP_i + \varepsilon_{it}, \quad (1)$$

where $Flight_{it}$ is the daily inbound flight frequency to country i on date t . The selected European countries in this study closed their borders to non-EU countries from 23 March 2020 onwards. Thus, $Travel\ Restriction$ is a dummy variable which is valued as one if the country has closed the border on date t , otherwise zero, and τ measures the average treatment effect in the regression discontinuity design. GDP_i is the Gross Domestic Product (GDP) of the destination country i which is a control variable and presents the accessibility of airports in the destination, because well-developed infrastructure can expand the capacity of the airports and infrastructure investment is a key component of GDP. Although Zhang, Zhang, Zhu, and Wang (2017) and Eric, Semeyutin, and Hubbard (2020) comprehensively discussed the determinants and measurements of airport accessibility and connectivity, since GDP is a cross-sectional variable in the panel model, other cross-sectional measurements for accessibility will be omitted due to the multicollinearity. Thus, only GDP is included in the model as a control variable.

In this research, R_t refers to the timeline and c stands for a specific time when the travel restriction comes into force. The causal effect of the travel restriction can be identified if we can observe the flight frequency of destination i on date t when the travel restriction is present and the same destination on the same date but with no travel restriction. Unfortunately, the two scenarios cannot be observed simultaneously. The general idea of regression discontinuity design is to use the observable outcome at the time only beyond c by a tiny margin to estimate the outcome on the other side of c (Lee & Lemieux, 2010). Since the margin limits to zero, the unobservable situation can be approximated on a local level around c . In the approximation process, it is assumed that all other factors on the two sides are identical except for the treatment variable (i.e. the presence or absence of the travel restriction). Thus, the difference in the flight frequency can only be caused by the presence of the travel restriction and the causal effect can be identified. $F(\cdot)$ is the function form of R_t , \ln is the natural-log algorithm and ε_{it} is the residual term.

The estimation of the local approximation can be achieved by parametric and nonparametric regressions, respectively (Lee & Lemieux, 2010). The parametric approach includes linear local regression and local polynomial regression, which is a more general model form (Lee & Lemieux, 2010). A more detailed introduction to regression discontinuity design can be found in Deng, Hu, and Ma (2019), which is the only published study to use regression discontinuity design in the tourism and hospitality literature at the time of writing.

Two-stage spatial Durbin model

A two-stage spatial Durbin model is further adapted to investigate the causal relationship between flight frequency and COVID-19 spread in selected European countries. The control of COVID-19 is a complex worldwide challenge which has not been solved yet. To eliminate the endogeneity issue caused by the omission of key determinants of the COVID-19 spread in the model, the 2019 flight frequency to the same destination on the same date is introduced as an instrumental variable to the 2020 flight frequency. As 2020 was a leap year, the data of 29 February was removed to match the 2019 data. The spatial Durbin model adopted in this study is specified as:

$$\begin{aligned} \ln(1 + Total\ Cases_{it}) = & constant + \rho \cdot W_{it} \cdot \ln(1 + Total\ Cases_{it}) \\ & + \sum_{j=1}^{14} \alpha_{1j} \ln Flight_{it} \cdot (1 - Travel\ Restriction) + \sum_{j=1}^{14} \beta_{1j} \ln Flight_{it} \cdot Travel\ Restriction + \gamma_1 \cdot \ln GDP_{it} \\ & + W_{it} \cdot \left[\sum_{j=1}^{14} \alpha_{2j} \ln Flight_{it} \cdot (1 - Travel\ Restriction) + \sum_{j=1}^{14} \beta_{2j} \ln Flight_{it} \cdot Travel\ Restriction + \gamma_2 \cdot \ln GDP_{it} \right] + \varepsilon_{it}, \end{aligned} \quad (2)$$

where W_{it} is the weight matrix measured by the passenger flows between countries. Compared with the matrix composed of the nearest neighbours, the passenger flows can present the different weights among neighbours and even the divergence between inbound and outbound flows from a country to another one. ρ measures the spillover effect of Covid-19 spreading from neighbouring countries to the focal country. α_{1j} and $W_{it} \cdot \alpha_{2j}$ stand for the impacts of the flight frequency on Covid-19 and the spillover effect of flight frequency in neighbouring countries on Covid-19 in the focal country before the travel restrictions started, respectively; whereas β_{1j} and $W_{it} \cdot \beta_{2j}$ stand for the same effects when the travel restriction is present, respectively. The European Centre for Disease Prevention and Control (ECDC) suggests that the incubation period of Covid-19 is up to 14 days (ECDC, 2020) and thus 14 lags are included in the model to draw a full picture of the impact of the flight frequency on the spread of Covid-19. GDP is introduced as a control variable to capture the heterogeneity across countries.

Data

The airline analysis is demand and supply orientated, evaluating the traffic from every continent to selected European countries from January 2019 to May 2020, while taking into account the changing dynamics associated with the COVID-19 pandemic. The supply data (i.e. flight frequency) was collected using the Official Airline Guide data, which records 96% of passenger itineraries and schedules of around 1000 airlines and more than 4000 airports. The dataset updates 57 million records of the flight status on a yearly basis and supports disaggregated analysis at the daily flight level. The Official Airline Guide data has been used in various academic papers (e.g. Akyildirim et al., 2020; Devriendt, Burghouwt, Derudder, De Wit, & Witlox, 2009; O'Connell & Connolly, 2016; Reynolds-Feighan, 2010; Zuidberg, 2019). This database does not include charter flights nor air cargo flights. The authors collected the daily supply data reported by origin-destination pairs from January 2019 to May 2020. We also measured the flight movements from a sample of observations (seven days) against a flight tracker database to determine the accuracy of

Official Airline Guide data, and we found that the data from Official Airline Guide was very accurate with almost identical correlations.

The demand data (i.e. passenger numbers) was collected using the Sabre AirVision Market Intelligence Data Tapes subscription database. The database collects data on weekly passenger demand, fares and airline revenues, but includes only indirect bookings such as those made with online travel agents and global travel retailers through a Global Distribution System. The provided data uses an algorithm that takes direct bookings into account to estimate the total demand, fares and revenues. The Sabre Market Intelligence Data Tapes database has also been extensively used in many academic papers (e.g. Derudder, Devriendt, & Witlox, 2010; Sismanidou, Tarradellas, Bel, & Fageda, 2013; Soyk, Ringbeck, & Spinler, 2018; Suau-Sanchez, Voltes-Dorta, & Rodríguez-Déniz, 2016). The authors collected the demand data reported by origin-destination pairs from January 2019 to May 2020. However, there were limitations associated with the Sabre Market Intelligence Data Tapes data as there is a time lag of three months before the data gets populated into the database, limiting the authors' ability to capture data only up to May 2020. In addition to the airline data, the total confirmed cases in selected European countries were collected from the European Centre for Disease Prevention and Control and the GDP data from the International Monetary Fund.

Findings and discussions

Results of regression discontinuity design analysis

The key assumption of regression discontinuity design is that the distribution of the dependent variable must be discontinuous around the cut-off point (Lee & Lemieux, 2010). A graphical method is used to identify the discontinuity of the flight frequency post lockdown, as suggested by Deng, Hu, and Ma (2019). In addition to the investigation of the flights to all selected European countries, the countries have been split into two groups which are the top 5 flight destinations and the rest (non-top 5) destinations in selected countries. The top 5 flight destinations in selected countries from January to May 2020 include the UK, Germany, Spain, Italy and France. The regression discontinuity design analysis was also conducted in the two groups to examine the robustness of the findings.

The distributions of all the selected markets, the top-5 European destinations and non-top 5 destinations are presented in Panels A–C, respectively, in Fig. 1. The left-hand side column lists the flight frequency distributions. Negative numbers on the horizontal axis stand for the number of days before the travel restrictions started (i.e. Day 0) whereas positive numbers indicate the number of days after the commencement of travel restrictions. The blue dots are the mean of bins, which are determined by the mimicking variance evenly-spaced method using spacings estimators (Calonico, Cattaneo, Farrell, & Titiunik, 2017). The number of bins and the bandwidth used in each model are listed in Table 1. Fig. 1 indicates that the discontinuity did not present on Day 0 because all the flights were scheduled in advance. Thus, the cut-off point emerged on the sixth day after the travel restrictions were implemented. A remarkable drop can be found in each panel around Day 6. Thus, it can be revealed that the effect of the travel restrictions on the flight frequency became evident from the sixth day after the restrictions were implemented on 23 March 2020.

The estimation results of the regression discontinuity design analysis are presented in Table 1, which includes both the non-parametric and parametric results. According to the pattern shown in Fig. 1, the quadratic function was used to estimate the model in the parametric methods. The McCrary (2008) test shows that the marginal density of R_i is continuous at a 5% significance level, thus we can focus on the identification of discontinuity around the cut-off point in the density function. The regression discontinuity design reveals that the implementation of the travel restrictions (τ) causally decreased the flight frequency in the 33 countries by 182 to 190 per day. In the top 5 European destinations, the decline in the number of flights could reach 562 to 656 per day, whereas in the non-top 5 destinations it was 105 to 109 per day. The median of the daily flight frequency in the 33 countries in the same time period for 2019 is 206, indicating that the travel restrictions froze 88% ($=182/206$) to 92% ($=190/206$) of the flights to selected European countries. This means that the European aviation industry almost came to a standstill due to the border closure, which indicates the enormous costs that the aviation industry paid to implement the travel restrictions.

The bandwidth is a critical hyperparameter to determine the regression discontinuity design result. The bandwidths selected for the full sample, the top 5 European destinations and non-top 5 destinations are as follows: 37.5, 28 and 35.6, respectively (see Table 1). To examine the robustness of the findings, the sensitivity test was conducted, which takes the selected bandwidth as the central point and moves to the left and right by four steps ahead with the step-length of 0.05. The sensitivity of the three models was examined by eight different bandwidths, respectively, and the estimation of the travel restriction's impact did not change at all, indicating a robust estimation result. The placebo test was also carried out by estimating the travel restrictions' impact with the 25% to 75% quantile values of the dates on the left- and right-hand sides of the cut-off points as fake cut-off points. As shown in the right-hand side column in Fig. 1, only the selected cut-off point date is significant at a 5% significance level, because zero is included in the 95% confidence interval (i.e. the shadow) in the rest of the cases. This means the causal effect presented on Day 6 is not a coincidence, and the implementation of the travel restrictions in Europe did causally decrease the flight frequency to all selected European destinations.

Results of the two-stage spatial Durbin model

When estimating the spatial Durbin model, the 2019 flight frequency was introduced as the instrumental variable of the 2020 flight frequency in the first stage. The predicted 2020 flight frequency generated by the 2019 data was input into the second stage

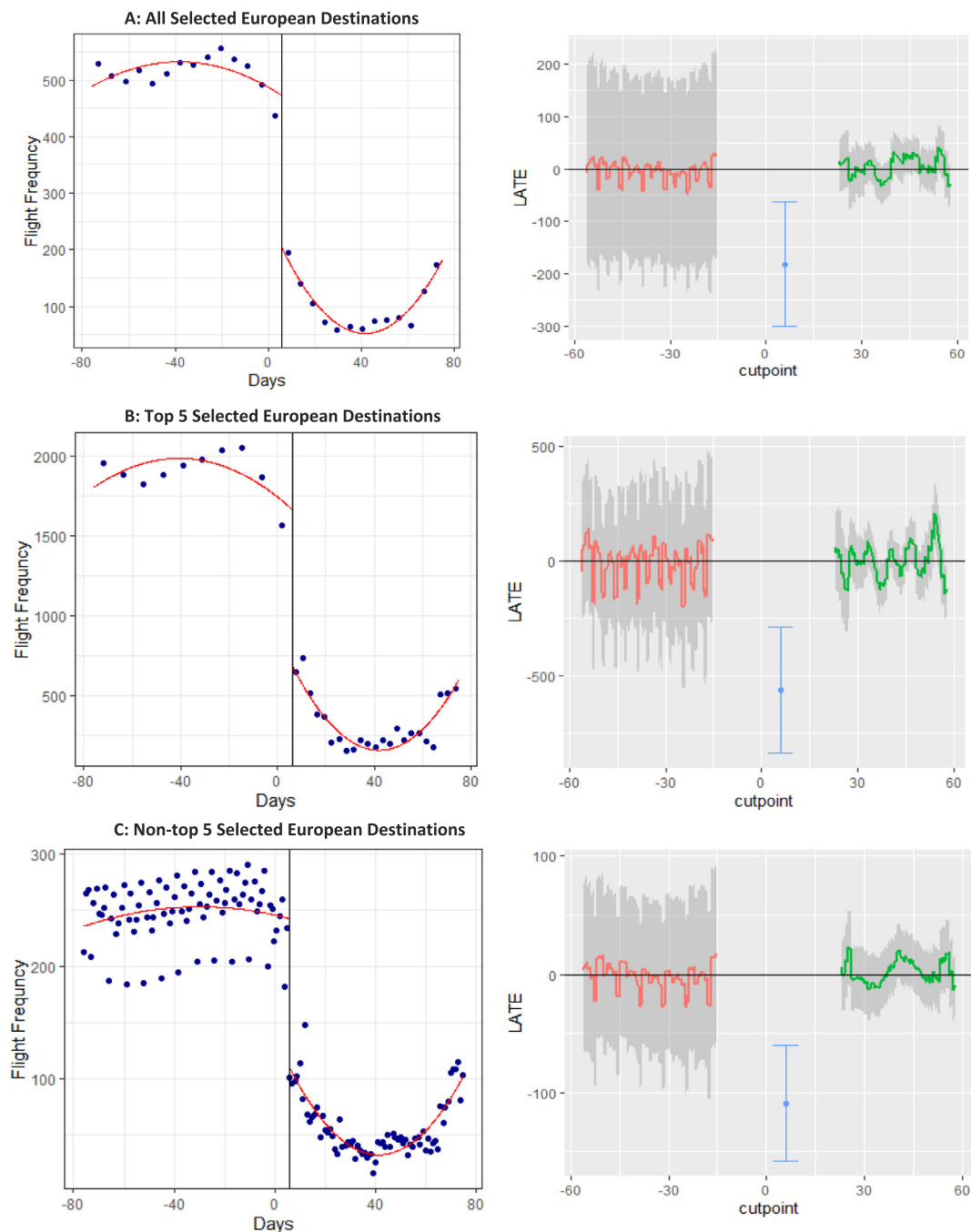


Fig. 1. Flight frequency distribution (left) and placebo test (right).

as independent variables to estimate the elasticities of the COVID-19 spread. The adoption of the instrumental variable can eliminate the endogeneity issue caused by the omission of other determinants of the COVID-19 development in the model. This is because the residual, which may be related to the dependent variable due to the omission of other independent variables, has been left in the first stage and independent variables input into the second stage model purely measure the impact of flight frequencies on COVID-19 development with the exclusion of the impact of other factors. The estimation results of the two stages are presented in Tables 2 and 3, respectively.

In the panel data analysis, to capture the impact of GDP across destinations, random effect models instead of fixed effect models are used: from one-step lagged (Lag_1) to 14-steps lagged (Lag_14) in the first stage. The estimation results of the first 13 steps are consistent with the coefficient of the 2019 flight ranges from 0.212 to 0.254 and GDP from 0.528 to 0.584. This means that the flight frequency of a destination in 2020 is positively related to the flight numbers on the same day in 2019

Table 1
Results of regression discontinuity design analysis.

	All selected European destinations		Top 5 European destinations		Non-top 5 European destinations	
	Non-parametric	Parametric	Non-parametric	Parametric	Non-parametric	Parametric
τ	−190.23** (−2.17)	−181.8** (−3.02)	−656.222** (−2.66)	−561.858*** (−4.00)	−104.97*** (−3.10)	−109.067*** (−4.34)
R_{t_left}		−12.071* (−2.21)		−56.400*** (−3.32)		−3.519 (−1.60)
$R^2_{t_left}$		−0.245 (−1.76)		−1.148* (−2.02)		−0.075 (−1.12)
R_{t_right}		0.371 (0.05)		8.375 (0.37)		−1.285 (−0.43)
$R^2_{t_right}$		0.451* (2.36)		2.071** (2.78)		0.147* (1.82)
GDP _i		0.004*** (7.68)		0.024* (2.43)		0.004*** (19.57)
Constant		285.4*** (5.95)		603.2** (3.04)		109.5*** (6.07)
R^2		0.179		0.812		0.368
F-statistic		84.04***		199.6***		178.8***
Number of bins		27		33		467
Bandwidth		37.5		28		35.6
McCrary Test	1.68		0.69		1.47	

Figures in parentheses are *t*-statistics.

* Represents significance at 5% level.

** Represents significance at 1% level.

*** Represents significance at 0.1% level.

and the GDP of the destination. In contrast, the 2019 flight in the 14-steps lag has a negatively marginal effect on the 2020 flight. Although the impact is marginal, the Wald X^2 test (282.04) is significant at the 0.1% level, indicating the overall significance of the 14-steps lagged model. Thus, the predicted 2020 flight frequency can still be used in the second stage.

The estimation results of the second stage are presented in Table 3. In this study, the top seven countries of origin are considered as neighbours of the focal destination in the spatial model. The analysis of the Sabre Market Intelligence Data Tapes data indicates that the top seven origin countries were all in Europe given the high travel demand between European countries. We also tested the top three and top five but, according to the Akaike information criterion and Bayesian information criterion, the top seven model showed the best model fit. Due to the limitations of space, the results of the models with the top three and the five neighbours are omitted. The Sargen's X^2 is zero, suggesting no overidentification issue in the model and thus, the model specification is correct (Sargen, 1958). The spillover effect of the dependent variable (ρ) is 0.648, indicating that a 1% increase in the

Table 2
Estimation results of the first stage.

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	Lag_6	Lag_7
ln (Flight_19)	0.221*** (5.84)	0.216*** (5.70)	0.221*** (5.82)	0.221*** (5.84)	0.212*** (5.61)	0.222*** (5.88)	0.223*** (5.91)
ln GDP	0.553*** (4.92)	0.562*** (5.00)	0.560*** (5.00)	0.562*** (5.02)	0.528*** (5.12)	0.564*** (5.09)	0.567*** (5.12)**
Constant	−2.321* (−2.12)	−2.377* (−2.18)	−2.372* (−2.18)	−2.386* (−2.20)	−2.442* (−2.25)	−2.400* (−2.23)	−2.415* (−2.25)
Wald X^2	87.65***	86.81***	88.94***	89.80***	87.35***	91.63***	92.84***
R^2	0.362	0.356	0.360	0.356	0.349	0.359	0.359
	Lag_8	Lag_9	Lag_10	Lag_11	Lag_12	Lag_13	Lag_14
ln (Flight_19)	0.222*** (5.88)	0.218*** (5.77)	0.220*** (5.81)	0.229*** (6.08)	0.235*** (6.29)	0.254*** (6.87)	−0.002*** (−16.50)
ln GDP	0.572*** (5.17)	0.581*** (5.24)	0.584*** (5.27)	0.580*** (5.26)	0.579*** (5.30)	0.564*** (5.25)	1.418*** (5.23)
Constant	−2.454* (−2.28)	−2.520* (−2.34)	−2.546* (−2.37)	−2.536* (−2.37)	−2.534* (−2.39)	−2.465* (−2.37)	−8.788*** (−3.20)
Wald X^2	93.23***	92.54***	93.73***	98.60***	102.88***	113.49***	282.04***
R^2	0.358	0.354	0.355	0.365	0.372	0.391	0.162

Figures in parentheses are *z*-statistics.

* Represents significance at 5% level.

** Represents significance at 1% level.

*** Represents significance at 0.1% level.

Table 3

Estimation results of spatial Durbin model.

			Two-stage estimation		One stage estimation	
			X	W.X	X	W.X
ρ			0.648*** (58.40)		0.524*** (37.30)	
Before travel restriction	ln (Lag_1)		−0.780 (−1.07)	−1.213 (−0.51)	−0.043 (−0.85)	−0.237* (−2.31)
	ln (Lag_2)		−0.509 (−0.66)	0.823 (0.28)	−0.006 (−0.11)	−0.047 (−0.38)
	ln (Lag_3)		0.835 (1.10)	−1.956 (−0.67)	−0.012 (−0.21)	0.019 (0.15)
	ln (Lag_4)		0.936 (1.26)	−1.488 (−0.51)	−0.047 (−0.80)	0.069 (0.54)
	ln (Lag_5)		−1.352 (−1.75)	−2.37 (−0.77)	−0.015 (−0.26)	−0.186 (−1.44)
	ln (Lag_6)		−1.705* (−2.36)	6.237* (2.30)	0.018 (0.31)	0.029 (0.22)
	ln (Lag_7)		0.517 (0.97)	−3.690* (−2.17)	−0.094 (−1.63)	−0.029 (−0.24)
	ln (Lag_8)		0.396 (0.54)	2.197 (0.91)	0.092 (1.60)	0.14 (1.020)
	ln (Lag_9)		−0.315 (−0.42)	−2.073 (−0.71)	−0.010 (−0.16)	−0.115 (−0.91)
	ln (Lag_10)		−0.692 (−0.93)	−0.521 (−0.18)	−0.008 (−0.13)	0.122 (0.94)
	ln (Lag_11)		−0.549 (−0.77)	−1.928 (−0.69)	−0.045 (−0.75)	−0.024 (−0.18)
	ln (Lag_12)		1.300 (1.91)	−0.581 (−0.21)	0.006 (0.10)	0.204 (1.50)
	ln (Lag_13)		1.902** (3.17)	−7.983*** (−3.47)	−0.031 (−0.53)	0.051 (0.37)
	ln (Lag_14)		−0.386*** (−4.69)	0.023 (0.20)	−0.005 (−0.09)	0.31** (2.73)
After travel restriction	ln (Lag_1)		1.090 (1.11)	2.526 (0.26)	−1.603*** (−3.46)	1.007 (1.49)
	ln (Lag_2)		0.543 (0.54)	3.332 (0.32)	−1.273** (−2.81)	0.631 (0.96)
	ln (Lag_3)		−1.262 (−1.27)	2.715** (0.27)	−0.311 (−0.68)	−0.806 (−1.20)
	ln (Lag_4)		0.195 (0.19)	8.079 (0.80)	−0.931* (−2.03)	−0.966 (−1.47)
	ln (Lag_5)		2.740** (2.66)	16.837 (1.69)	−0.598 (−1.31)	−1.006 (−1.49)
	ln (Lag_6)		3.504*** (3.53)	16.680 (1.93)	−0.803 (−1.76)	−0.575 (−0.85)
	ln (Lag_7)		−0.653 (−0.93)	−2.899 (−1.44)	−0.422 (−0.91)	−0.427 (−0.62)
	ln (Lag_8)		−1.030 (−1.00)	−4.109 (−0.43)	1.282* (2.85)	−0.852 (−1.28)
	ln (Lag_9)		−0.195 (−0.19)	−7.001 (−0.69)	1.004* (2.23)	−0.495 (−0.75)
	ln (Lag_10)		1.290 (1.26)	−5.111 (−0.52)	0.306 (0.68)	0.775 (1.16)
	ln (Lag_11)		−1.061 (−1.05)	−10.588 (−1.10)	0.751 (1.66)	1.147 (1.77)
	ln (Lag_12)		−2.103* (−2.18)	−17.763* (−1.99)	0.420 (0.93)	1.089 (1.65)
	ln (Lag_13)		−3.709*** (−4.27)	−15.942* (−2.16)	0.525 (1.16)	0.943 (1.42)
	ln (Lag_14)		−0.128 (−1.35)	0.044 (0.28)	0.656 (1.40)	0.315 (0.46)
ln GDP			1.298* (2.04)	10.153** (2.89)	1.181 (2.24)*	0.314 (0.09)
Constant			−42.733 (−1.23)		−15.366 (−0.43)	
R^2			0.234		0.356	
Log-likelihood			−5574.08		−5503.04	
AIC			11,272.16		11,241.39	
BIC			11,661.89		11,668.84	

Figures in parentheses are z-statistics.

* Represents significant at 5% significant level.

** Represents significant at 1% significant level.

*** Represents significant at 0.1% significant level.

confirmed cases of COVID-19 in neighbouring countries would lead to an increase in the confirmed cases by 0.648% in the focal country. Although most coefficients of the flight frequency are not significant, by aggregating all the significant elasticities, the overall elasticity of the flight frequency when the travel restriction is present is 0.431, suggesting that a 1% decrease in the flight frequency to a destination can help to reduce the number of confirmed COVID-19 cases by 0.431%.

COVID-19 confirmed cases because it is predicted by the 2019 flight frequency and the pandemic did not exist in 2019. However, the overall elasticity and Table 3 indicate a significant relationship between the 2019 predicted data and the 2020 COVID-19 spread. The only possible reason for this would be that the 2020 flight frequency could have caused the change to the COVID-19 spread because it is correlated with the 2019 frequency as shown in the first stage results (Table 2). The two-stage spatial Durbin model reveals that the decline in flight frequency can causally limit the spread of COVID-19. The last two columns in Table 3 present the estimation results of the one-stage approach. Although the R^2 is larger than the two-stage approach and the Akaike information criterion and Bayesian information criterion suggest a preferable model fit, the overall elasticity under the one-stage model is −1.52. This means that the decrease in flight frequency could lead to an increase in the number of COVID-19 confirmed cases, which is counter intuitive and may be caused by the endogeneity in the model. Thus, this further supports the use of the two-stage approach to estimate the spatial Durbin model and eliminate the endogeneity issue.

Counterfactual analysis

In the spatial Durbin model, marginal effects are estimated to reveal the spatial feedback loop effects which identify the average effect of the flight frequency on the pandemic spread from a destination to other neighbouring destinations (Kim, Williams, Park, & Chen, 2020; LeSage & Pace, 2009). The average total effects of the 31 destinations across lag periods are presented in Fig. 2 where the shadow represents the 5% significance intervals. The overall elasticity of the total effect is 0.908, indicating that on average, a 1% decrease in flight frequency can lead to a 0.908% decrease in the confirmed COVID-19 cases.

The counterfactual analysis can be carried out based on the estimated total effect. As shown in Fig. 3, if selected European countries have not restricted travel, then the peak of the daily confirmed cases would have surged up to 62,211 by 1 April 2020, which is 70% more than the actual number of cases recorded on the same date. As a result, the total confirmed cases would have expanded to 2.28 million in selected European countries by the end of May, which is 62% greater than the actual statistics. Compared with the same period in 2019, 795,088 flights were cancelled in selected European countries. The incidence rate of COVID-19 in selected countries was 11.7% by the end of May 2020 (ECDC, 2020), which implies that the aviation industry was able to directly save 101,309 ($= [2.28 \text{ million} - 1.41 \text{ million}] * 11.7\%$) lives as a result of 795,088 cancelled flights and significant travel restrictions. If the multiplier effect of the virus spread is considered, the total confirmed cases and lives saved by the aviation sector would further increase.

Conclusions

The COVID-19 pandemic has had a devastating impact on the global air transport and tourism industries as governments around the world have imposed a plethora of restrictions that have included travel bans, lockdowns, stay-at-home directives as well as quarantine rules in order to prevent the rapid spread of the disease. These policies have had a catalytic negative impact as they have caused global air travel to severely recede to unprecedented levels, with, for example, traffic falling by around 70% by May 2020 from the previous 12 months as people were reluctant and unable to travel due to different travel restrictions measures in various countries.

This paper has examined the causal impact of the travel restrictions on the flight frequency in selected European countries by using a quasi-experimental regression discontinuity design method, and further its consequential impact on the spread of COVID-19 using a two-stage SDM. The findings have shown that there was a significant reduction in the flight frequency to all selected European countries six days after they implemented travel restrictions. Such a reduction in flights by 1% helped reduce the number of confirmed COVID-19 cases by 0.431%, according to the two-stage spatial Durbin model estimation. In addition, counterfactual analysis has inferred that when considering the spillover effects of flight frequency on the pandemic spread from one destination to its neighbour, and vice versa, a 1% decrease in flight frequency reduced the number of confirmed cases by 0.908%. This further implies that if there had not been any travel restrictions in selected European countries, then on 1 April 2020, the number of confirmed cases would have been higher by 62,211 cases. From the start of the first lockdown in March to the end of May 2020, the aviation industry in selected European countries cancelled 795,000 flights, which resulted in avoiding another six million people becoming infected and saved 101,309 lives. The number of people actually infected with the virus in Europe was around 2.1 million by May 2020 according to ECDC, and this would have been a lot higher if the number of flights had not been curtailed so rapidly.

This study demonstrates significant theoretical contributions by, first, estimating the causal relationship between travel restrictions and flight frequency, and, further, its consequential impact on COVID-19 across European countries. Previous studies have shown the importance of flight and travel restrictions in reducing the inter-regional spread of infectious diseases (Brownstein, Wolfe, & Mandl, 2006; Hufnagel, Brockmann, & Geisel, 2004; Tuncer & Le, 2014), and there have also been counter arguments regarding the effectiveness of travel restrictions in controlling the spread (Chinazzi et al., 2020; Cooper, Pitman, Edmunds, & Gay, 2006; Ferguson et al., 2006). Yet, the diversity in the study context (e.g. type of disease, national context, domestic v. international travel) has resulted in different conclusions being drawn. This study significantly contributes to the crisis management theory in the tourism literature, confirming the causal impact of travel restrictions on the fall in flight frequency and its consequential

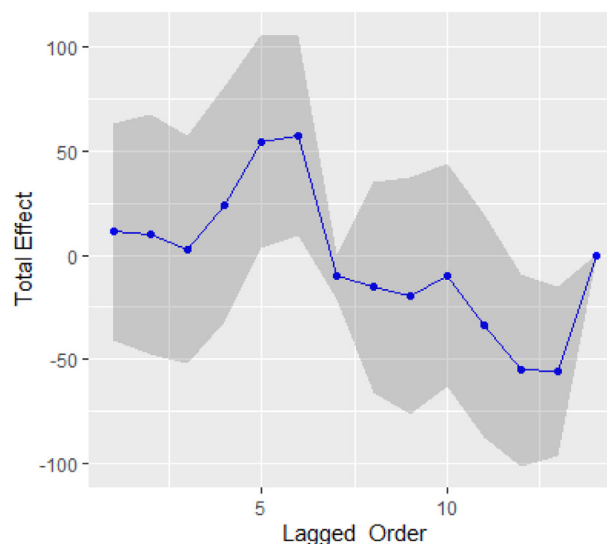


Fig. 2. Total effects of the spatial Durbin model.

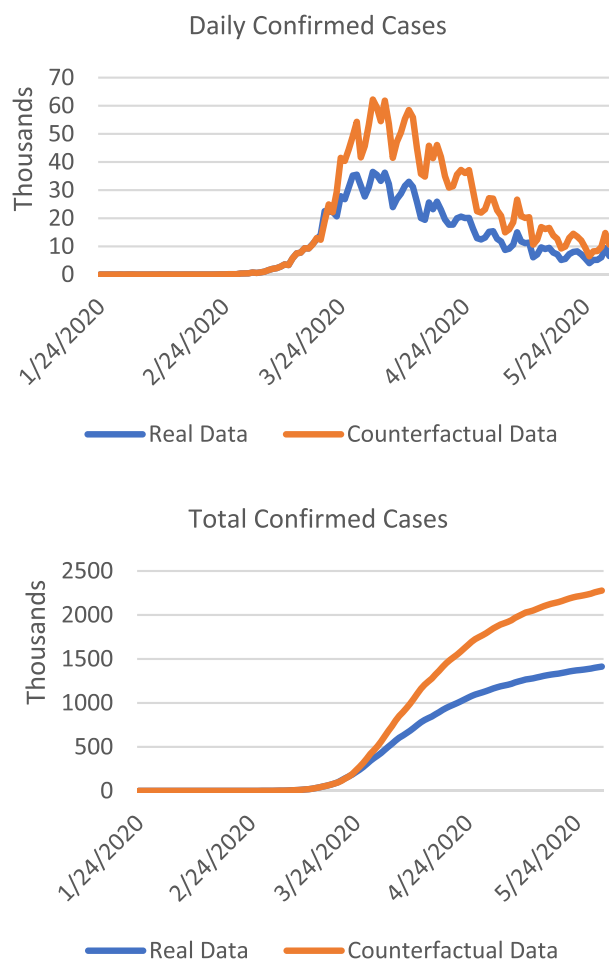


Fig. 3. Counterfactual analysis of the COVID-19 spread in selected European countries.

impact on reducing the number of COVID-19 cases in the context of Europe. To the best of the researchers' knowledge, this is one of the few tourism studies that look at the impact of COVID-19 on the aviation industry, particularly on flight frequency and its impact on the spread of the virus.

Second, from the methodological perspective, there is a limited application of quasi-experimental methods, which can estimate counterfactual effects, in the tourism literature. This study has used regression discontinuity design to estimate the impact of travel restrictions on flight frequency and further, a two-stage spatial modelling using an instrumental variable to examine the consequential impact on the number of infected cases in order to understand the implications of travel restrictions on the number of lives saved by restricting international flights. There is also limited application of spatial models in the context of the aviation industry, and the current study has employed a two-stage spatial Durbin model to examine the causal impact of the flight frequency on the number of infected cases by introducing the instrumental variable into the model (before and after the travel restrictions were put in place) in order to empirically illustrate the contribution of aviation related travel restrictions to control the spread of COVID-19.

Based on the findings, the implications for the aviation industry can be perceived as a double-edged sword in that on one side, such restrictions on people's movements across national borders can effectively control the spread of the pandemic and save lives (Luo, Imai, & Dorigatti, 2020; Vaidya, Herten-Crabb, Spenser, Moon, & Lillywhite, 2020), yet, on the other side, drastic yet inevitable flight cancellations have damaged the industry. However, empirical evidence shows that the aviation industry has effectively reduced the spread of COVID-19 by severely curtailing its flights and commercial operations, which has potentially saved lives. Thus, the findings of this study can be used to assess the lockdown policy effectiveness from the aviation perspective and serve as empirical support to help governments develop future pandemic control policies.

In addition, when governments impose such stringent restrictions that ultimately lead to an unprecedented shut-down of the airline industry, then the argument for government financial support increases. The overall financial cost of this pandemic has been catastrophic for the global airline industry as their losses are expected to be over four times those sustained after the global financial crisis of 2009, implying that their aggregated profits since the birth of aviation will be eliminated, leaving a zero net gain when factoring in the last one hundred years of operations. Governments worldwide are scrambling to shore up their finances by pumping billions of dollars

into their national carrier in return for equity, while also giving tax-free loans, deferred taxes and loan guarantees. The carnage resulting from the pandemic is evident and as Czerny, Fu, Lei, and Oum (2021) established, 19 airlines filed for bankruptcy during the period between March and early July 2020 with varying fleet sizes ranging from just six aircraft to as many as 315 aircraft. The industry remains in a perilous state of flux. Both the industry and policymakers should strategically plan how to better support the resilience of the industry in times of crisis when travel restrictions are implemented but also to manage the costs of such implementation of the control measures and the competitiveness of airlines post-pandemic (Kim, Liu, & Williams, 2021).

The limitations of this research are acknowledged. Considering the evolution of COVID-19, to date, there has already been a second wave in many European countries and different levels and types of government support have been provided for the aviation and tourism industry, which were not considered when conducting the research. Future research can consider different waves of the pandemic and government support and further examine the impact of different levels of restrictions by country and time, which could not be considered in the current study due to data unavailability. This study has only focussed on Europe and Europe inbound and intra-Europe flights, but it is acknowledged that other forms of mobility such as daily and domestic mobility facilitate the spread of the virus and have an impact on the tourism industry. Future research could explore different forms of mobility and their implications for the tourism industry in different regions. From the methodological perspective, fuzzy regression discontinuity design can be used in future research to identify the causal effect when the assignment of the treatment is also determined by other unobservable factors. In addition, a more comprehensive analysis in future studies that consider both the positive (e.g. saving lives) and negative (e.g. financial costs) effects of travel restrictions could generate a more complete picture of the net impact of travel restrictions on the aviation industry, which would be more informative for policy evaluation and industrial strategy development.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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